# Task\_3\_Prodigy\_internship

June 4, 2024

### PRODIGY INFOTECH DATA SCIENCE INTERN

#TASK 3

TASK OVERVIEW: Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

### IMPORTING THE LIBRARIES AND DATASET

```
[]: import numpy as np
  import pandas as pd
  import matplotlib.pyplot as plt
  import seaborn as sns
  from sklearn.model_selection import train_test_split
```

[]: df = pd.read\_csv("/content/bank marketing dataset.csv")

#### DATA PREPROCESSING

```
[]: df.head()
```

[]:	age	job	marital	education	default	balance	housing	loan	contact	\
0	59	admin.	${\tt married}$	secondary	no	2343	yes	no	unknown	
1	56	admin.	${\tt married}$	secondary	no	45	no	no	unknown	
2	41	technician	${\tt married}$	secondary	no	1270	yes	no	unknown	
3	55	services	${\tt married}$	secondary	no	2476	yes	no	unknown	
4	54	admin.	married	tertiary	no	184	no	no	unknown	

	day	month	duration	campaign	pdays	previous	poutcome	deposit
0	5	may	1042	1	-1	0	unknown	yes
1	5	may	1467	1	-1	0	unknown	yes
2	5	may	1389	1	-1	0	unknown	yes
3	5	may	579	1	-1	0	unknown	yes
4	5	may	673	2	-1	0	unknown	yes

### []: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11162 entries, 0 to 11161

```
Data columns (total 17 columns):
                    Non-Null Count Dtype
     #
         Column
                     -----
     0
         age
                    11162 non-null
                                     int64
     1
                                     object
         job
                    11162 non-null
     2
         marital
                    11162 non-null
                                     object
     3
         education
                    11162 non-null
                                     object
         default
                    11162 non-null
                                     object
     5
         balance
                    11162 non-null int64
     6
                    11162 non-null
                                     object
         housing
     7
                    11162 non-null
         loan
                                     object
     8
         contact
                    11162 non-null
                                     object
     9
                                     int64
         day
                    11162 non-null
         month
     10
                    11162 non-null
                                     object
     11
         duration
                    11162 non-null
                                     int64
     12
         campaign
                    11162 non-null
                                     int64
     13
         pdays
                    11162 non-null
                                     int64
     14
         previous
                    11162 non-null
                                     int64
     15
         poutcome
                    11162 non-null
                                     object
         deposit
                    11162 non-null
                                     object
    dtypes: int64(7), object(10)
    memory usage: 1.4+ MB
[]: df.nunique()
[]: age
                    76
     job
                    12
    marital
                     3
     education
                     4
     default
                     2
                  3805
     balance
                     2
     housing
                     2
     loan
                     3
     contact
                    31
     day
                    12
     month
                  1428
     duration
                    36
     campaign
                   472
     pdays
     previous
                    34
                     4
     poutcome
                     2
     deposit
     dtype: int64
```

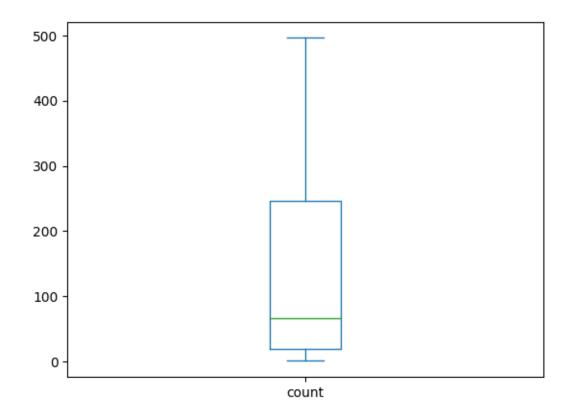
[]: df.duplicated()

```
[]:0
              False
              False
     1
    2
              False
     3
              False
     4
              False
     11157
             False
     11158
              False
     11159
              False
     11160
              False
              False
     11161
     Length: 11162, dtype: bool
[]: df.columns
[]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
            'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
            'previous', 'poutcome', 'deposit'],
           dtype='object')
[]: df.isnull().sum()
[]: age
                  0
     job
                  0
    marital
                  0
     education
                  0
    default
                  0
    balance
                  0
    housing
                  0
    loan
                  0
     contact
                  0
     day
                  0
    month
                  0
    duration
                  0
                  0
     campaign
    pdays
                  0
    previous
                  0
                  0
    poutcome
                  0
     deposit
    dtype: int64
    EDA
[]: age_value = df['age'].value_counts()
     age_value
```

```
[]: age
     31
           496
     32
           477
     34
           466
           464
     33
     35
           461
             2
     92
     93
             2
     88
             2
     95
             1
     89
             1
     Name: count, Length: 76, dtype: int64
```

# []: age\_value.plot(kind="box")

# []: <Axes: >



```
[]: sns.distplot(df['age'])
  plt.title("age distribution")
  plt.xlabel("age")
  plt.ylabel('values')
```

<ipython-input-12-f0501e0852cd>:1: UserWarning:

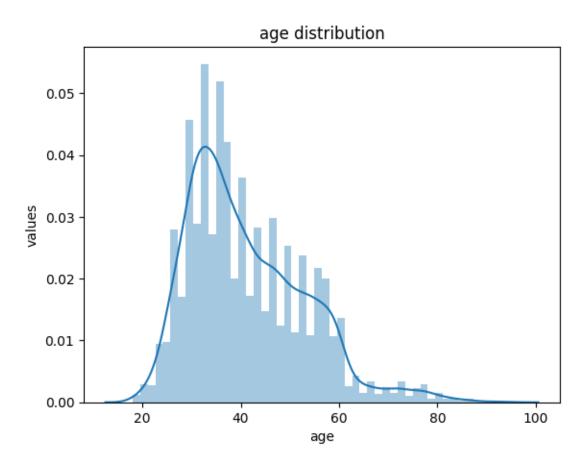
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df['age'])

[]: Text(0, 0.5, 'values')



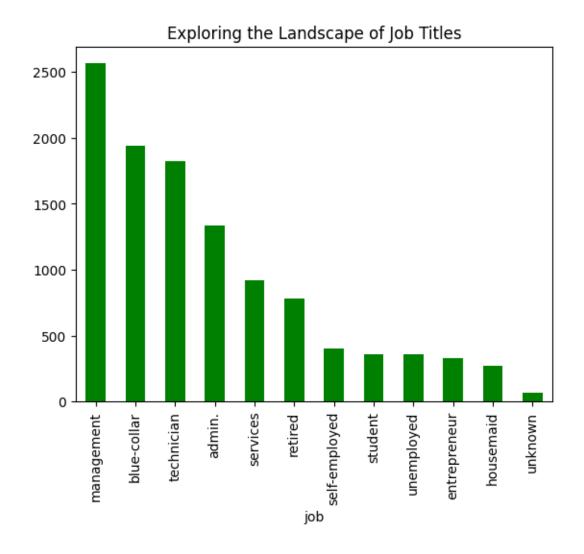
```
[]: [job = df['job'].value_counts()
    job
```

[]: job management 2566 blue-collar 1944

```
1823
technician
admin.
                  1334
services
                   923
retired
                   778
self-employed
                   405
student
                   360
unemployed
                   357
entrepreneur
                   328
                   274
housemaid
unknown
                    70
Name: count, dtype: int64
```

```
[]: job.plot(kind="bar",color='green')
plt.title("Exploring the Landscape of Job Titles")
```

[]: Text(0.5, 1.0, 'Exploring the Landscape of Job Titles')

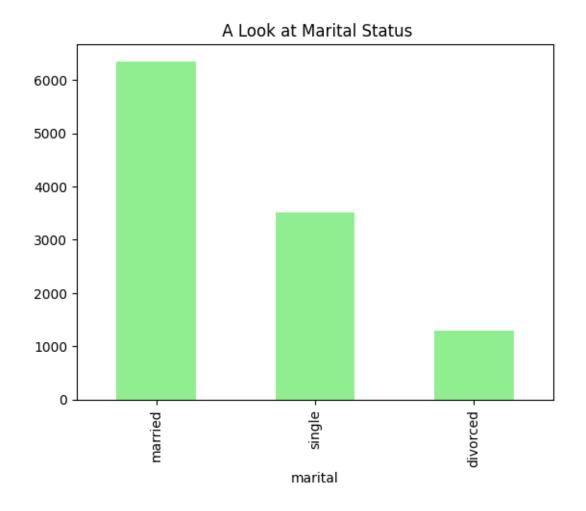


```
[]: marital_status = df['marital'].value_counts()
    marital_status

[]: marital
    married 6351
    single 3518
    divorced 1293
    Name: count, dtype: int64

[]: marital_status.plot(kind="bar",color='lightgreen')
    plt.title(" A Look at Marital Status")
```

[]: Text(0.5, 1.0, ' A Look at Marital Status')

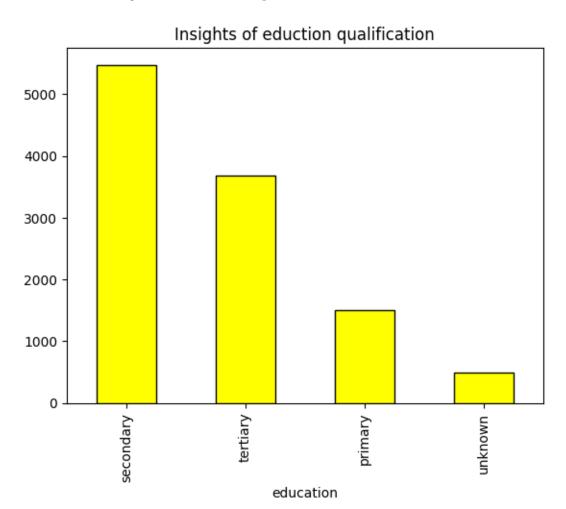


```
[]: education_distribution = df['education'].value_counts()
education_distribution
```

[]: education
secondary 5476
tertiary 3689
primary 1500
unknown 497
Name: count, dtype: int64

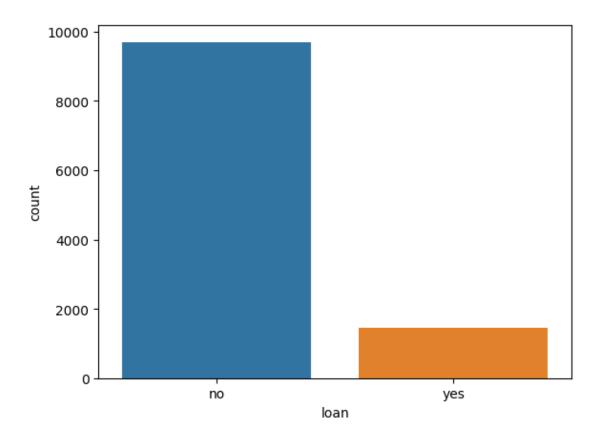
[]: education\_distribution.plot(kind="bar",color="yellow",edgecolor="black")
plt.title("Insights of eduction qualification")

[]: Text(0.5, 1.0, 'Insights of eduction qualification')



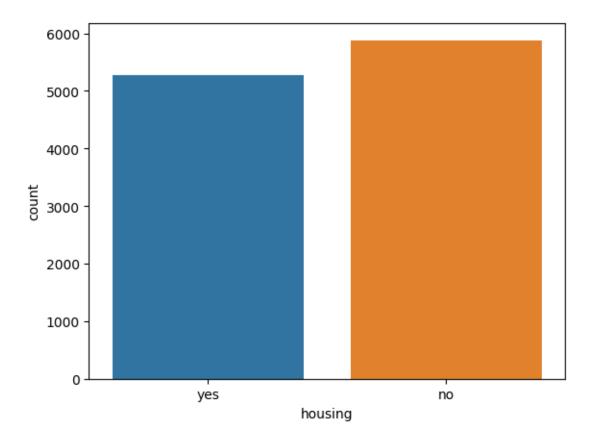
```
[]: sns.countplot(x="loan",hue="loan",data=df)
```

[]: <Axes: xlabel='loan', ylabel='count'>



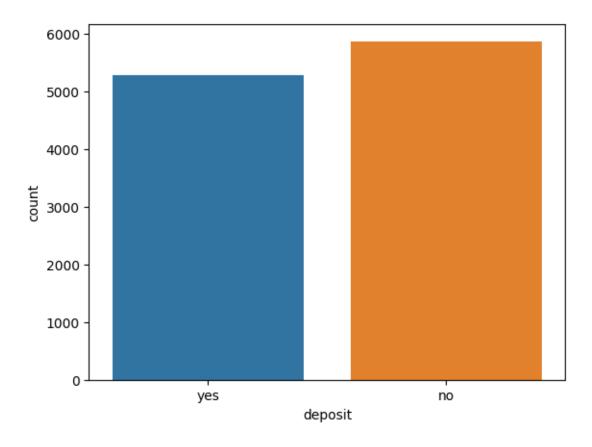
```
[]: sns.countplot(x="housing",hue="housing",data=df)
```

[]: <Axes: xlabel='housing', ylabel='count'>



```
[]: sns.countplot(x="deposit",hue="deposit",data=df)
```

[]: <Axes: xlabel='deposit', ylabel='count'>



## Feature Engineering

```
[]: import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Using Label Encoder
label_encoder = LabelEncoder()
df_label_encoded = df.copy()
df_label_encoded["job"] = label_encoder.fit_transform(df["job"])
df_label_encoded["marital"] = label_encoder.fit_transform(df["marital"])
df_label_encoded["education"] = label_encoder.fit_transform(df["education"])
df_label_encoded["default"] = label_encoder.fit_transform(df["default"])
df_label_encoded["deposit"] = label_encoder.fit_transform(df["deposit"])
df_label_encoded["loan"] = label_encoder.fit_transform(df["loan"])
df_label_encoded["housing"] = label_encoder.fit_transform(df["housing"])
print("Label Encoded Data:")
print(df_label_encoded)
```

```
Label Encoded Data:
```

```
age job marital education default balance housing loan \setminus 0 59 0 1 1 0 2343 1 0
```

```
2
              41
                     9
                               1
                                            1
                                                      0
                                                             1270
                                                                           1
                                                                                  0
    3
              55
                     7
                               1
                                            1
                                                      0
                                                             2476
                                                                           1
                                                                                  0
    4
              54
                     0
                               1
                                            2
                                                      0
                                                              184
                                                                           0
                                                                                  0
              •••
    11157
              33
                               2
                                            0
                                                      0
                                                                 1
                                                                           1
                                                                                  0
                     1
    11158
              39
                     7
                               1
                                            1
                                                      0
                                                              733
                                                                           0
                                                                                  0
    11159
                               2
                                                      0
                                                                           0
                                                                                  0
              32
                     9
                                                                29
    11160
              43
                     9
                               1
                                            1
                                                      0
                                                                 0
                                                                           0
                                                                                  1
    11161
              34
                     9
                               1
                                            1
                                                      0
                                                                 0
                                                                           0
                                                                                  0
              contact
                        day month
                                     duration
                                                campaign
                                                            pdays
                                                                    previous poutcome
    0
                                                                            0
              unknown
                          5
                                          1042
                                                        1
                                                               -1
                                                                                unknown
                               may
    1
                           5
                                          1467
                                                         1
              unknown
                                                               -1
                                                                            0
                                                                                unknown
                               may
    2
              unknown
                          5
                                          1389
                                                         1
                                                               -1
                                                                            0
                                                                                unknown
                               may
    3
              unknown
                          5
                                           579
                                                        1
                                                               -1
                                                                            0
                                                                                unknown
                               may
    4
              unknown
                          5
                               may
                                           673
                                                         2
                                                               -1
                                                                                unknown
    11157
             cellular
                         20
                                           257
                                                         1
                                                               -1
                                                                            0
                                                                                unknown
                               apr
    11158
                                                         4
                                                                            0
                                                                               unknown
              unknown
                         16
                               jun
                                            83
                                                               -1
                                                        2
    11159
             cellular
                                                               -1
                                                                                unknown
                         19
                               aug
                                           156
                                                                            0
                                                         2
    11160
             cellular
                          8
                                             9
                                                              172
                                                                            5
                                                                                failure
                               may
    11161
             cellular
                                                         1
                                                               -1
                                                                                unknown
                               jul
                                           628
             deposit
    0
                    1
    1
                    1
    2
                    1
    3
                    1
    4
                    1
    11157
                   0
    11158
                    0
    11159
                    0
    11160
                    0
    11161
                    0
     [11162 rows x 17 columns]
[]: df_label_encoded.
       Godrop(columns=['contact','day','month','duration','poutcome'],inplace=True)
[]: df_label_encoded
[]:
                         marital
                                   education
                                                default
                                                          balance
                                                                     housing
                                                                               loan
                                                                                      \
                   job
             age
              59
                     0
                                                              2343
     0
                                1
                                             1
                                                       0
                                                                            1
                                                                                   0
                                1
                                             1
                                                       0
                                                                            0
     1
                     0
                                                                45
                                                                                   0
              56
```

2	41	9	1	1	0	1270	1	0
3	55	7	1	1	0	2476	1	0
4	54	0	1	2	0	184	0	0
	•••	•••	•••		•••	•••		
11157	33	1	2	0	0	1	1	0
11158	39	7	1	1	0	733	0	0
11159	32	9	2	1	0	29	0	0
11160	43	9	1	1	0	0	0	1
11161	34	9	1	1	0	0	0	0

	campaign	pdays	previous	deposit
0	1	-1	0	1
1	1	-1	0	1
2	1	-1	0	1
3	1	-1	0	1
4	2	-1	0	1
•••		••		
11157	1	-1	0	0
11158	4	-1	0	0
11159	2	-1	0	0
11160	2	172	5	0
11161	1	-1	0	0

[11162 rows x 12 columns]

# Train test Spliting

```
[]: x = df_label_encoded.drop("deposit",axis=1)
```

[]: x

[]:		age	job	marital	education	default	balance	housing	loan	\
	0	59	0	1	1	0	2343	1	0	
	1	56	0	1	1	0	45	0	0	
	2	41	9	1	1	0	1270	1	0	
	3	55	7	1	1	0	2476	1	0	
	4	54	0	1	2	0	184	0	0	
		•••	•••		•••	•••				
	11157	33	1	2	0	0	1	1	0	
	11158	39	7	1	1	0	733	0	0	
	11159	32	9	2	1	0	29	0	0	
	11160	43	9	1	1	0	0	0	1	
	11161	34	9	1	1	0	0	0	0	

campaign pdays previous
0 1 -1 0
1 1 -1 0

```
2
     11157
                   1
                         -1
                                    0
     11158
                         -1
                                    0
                   4
     11159
                   2
                         -1
                                    0
     11160
                   2
                        172
                                    5
                   1
     11161
                         -1
     [11162 rows x 11 columns]
[]: y = df_label_encoded['deposit']
[]: y
[]: 0
              1
              1
     2
              1
     3
              1
              1
     11157
              0
     11158
     11159
     11160
     11161
    Name: deposit, Length: 11162, dtype: int64
[]: x_train, x_test, y_train, y_test = train_test_split (x,y,test_size=0.
      →2,random_state=2)
[]: x_train.shape
[]: (8929, 11)
[]: x_test.shape
[]: (2233, 11)
[]: y_train.shape
[]: (8929,)
[]: y_test.shape
[]: (2233,)
```

-1

-1

#### MODEL TRAINING

```
[]: from sklearn.tree import DecisionTreeClassifier
     dt_model = DecisionTreeClassifier()
[]: dt_model.fit(x_train,y_train)
[ ]: DecisionTreeClassifier()
[]: from sklearn.metrics import confusion_matrix, accuracy_score,__
      ⇔classification_report
    MODEL EVALUATION
[]: confusion_matrix = pd.
      →DataFrame(confusion_matrix(y_test,y_pred),columns=['Predicted No','Predicted_

¬Yes'],index=['Actual No','Actual Yes'])
[]: confusion_matrix
                Predicted No Predicted Yes
[]:
     Actual No
                          711
                                         476
     Actual Yes
                          458
                                         588
[]: y_pred = dt_model.predict(x_test)
[]: print(classification_report(y_test,y_pred))
                  precision
                               recall f1-score
                                                  support
               0
                       0.61
                                 0.60
                                           0.60
                                                      1187
                       0.55
                                 0.56
                                                      1046
               1
                                           0.56
                                           0.58
                                                      2233
        accuracy
                                           0.58
                                                      2233
       macro avg
                       0.58
                                 0.58
    weighted avg
                       0.58
                                 0.58
                                           0.58
                                                      2233
[]: print("Decision Tree Classifier")
     print(f"Accuracy:{accuracy_score(y_test,y_pred)}",)
    Decision Tree Classifier
```

Accuracy:0.5817286162113748